Automatic Identification and Recording of Cardiac Arrhythmia

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Abstract

ECG waveform data showing the spontaneous evolution of ventricular fibrillation (VF) together with its precursors in humans is rare. When such data has been obtained, the resolution is often poor, or the length of pre-onset recording is limited. We describe a new automatic data collection facility that is capable of recording such data. We designed computer software that, in conjunction with Hewlett-Packard proprietary hardware, allows continuous monitoring of physiological waveforms from up to 24 separate hospital beds. Episodes of cardiac arrhythmia (including ventricular tachycardia and ventricular fibrillation) are identified online by either power spectral analysis or nonlinear complexity algorithm. Each episode is automatically recorded for 20 minutes with 10 minutes both before and after onset of the arrhythmia. When monitoring a 6-bed coronary care unit this facility will typically collect around 10-50 recordings per week. The majority of these will be artifacts. However, 2-8 genuine VF episodes will also be recorded per month.

1. Introduction

The mechanism underlying spontaneous evolution of ventricular fibrillation (VF) is poorly understood. Algorithmic methods to predict imminent arrhythmia require large data banks of representative time series showing spontaneous evolution of arrhythmia. However, such time series are particularly rare.

Time series showing the evolution of VF are often recorded by implantable defibrillators (for example [1]). This data is often noisy, may only represent the sequence of RR intervals and is typically morphologically different from surface electrocardiogram (ECG) recordings.

In 1991 Clayton and colleagues [2] described a solution for in-hospital monitoring of ECG and automatic recording of VF. Clayton's data acquisition system required a dedicated computer, hardware arrhythmia trigger and associated software for each bedside monitor in a 10-bed coronary care unit (CCU). Computational limitations of the time meant that 1-minute of pre-VF (along with 4 minutes of post-VF) could be recorded at 250 Hz for each trigger event.

In this paper we describe a new data acquisition system. This system requires a single, dedicated personal computer (PC) that is connected to a hospital CCU network, and is capable of recording up to 45 minutes of pre-arrhythmia (along with post-arrhythmia) data at a resolution of 800 Hz at 10 bits (or 125 Hz at 12 bits). Because the system is connected via a local network to the CCU computers and bedside monitors, the hardware may be located at a physically separate site. Hence there is virtually no interruption to the normal running of the CCU.

In the remainder of this section we provide an overview of the necessary hardware and software. In Section 2 we provide a more detailed discussion of our algorithm. Section 3 provides some representative results, and in Section 4 we make some concluding remarks.

1.1. Hardware

Our data acquisition software runs on a low-end Hewlett-Packard (HP) Vectra PC (any PC with an ISA/EISA bus, capable of running Windows NT would be sufficient). ECG waveform data is collected by an assortment of bedside monitors that are connected to a HP Serial Distribution Network (SDN). The SDN is a local medical communications network connecting bedside monitors, patient information centers and computer systems. For example, the SDN in a single ward is responsible for collating and displaying patient information and waveforms on a single central console.

To allow for communication between our data acquisition system and the SDN, the PC was fitted with a programmable Speedy SDN interface card (HP 78360B). An overview of the required hardware interaction and data transmission is provided in Figure 1.

The Speedy SDN interface card and SDN network allow for data acquisition at a resolution of either 500 Hz at 10 bits or 125 Hz at 12 bits. For our data collection protocol we have chosen to collect data at the higher temporal rate of 500 Hz.
1.2. Software

The HP Speedy SDN interface card is a programmable interface card that allows for communication between a host PC and a SDN. Control messages and data are requested by the Speedy card, the responses are read from the SDN and transmitted to the host PC by the Speedy card. The Speedy card communicates with the host PC using an extremely low-level protocol (consisting of 16 bit words) via direct memory access (DMA).

Our custom software requests ECG waveform data from each bed connected to the SDN. Bedside monitors able to provide ECG waveform data then transmit this (via the Speedy SDN card) to the host PC. Using either a spectral power analysis algorithm [2,3] or a nonlinear complexity estimation algorithm [4] the host PC calculates a statistical quantity from the data. If this quantity exceeds a threshold the recording is automatically triggered.

Once recording is triggered the memory buffer containing the historical data (up to approximately 45 minutes pre-trigger) is written to disk along with a predefined length of post-trigger data. Available patient information (i.e. name, patient specific hospital identification number, and bed number/location) is also recorded in the data file.

Recorded data files can then be copied to a remote computer for subsequent off-line analysis.

2. Algorithms

The data acquisition algorithms must achieve four main tasks: (1) periodic interrogation of the SDN (via the Speedy card) to determine which beds are occupied, by whom, and if ECG waveform data is being monitored, (2) continuous monitoring of ECG data from all beds of interest, (3) testing a trigger criterion to determine when to record data, and (4) record data in response to a trigger.

The first two tasks are a straightforward programming exercise. It is worth stating that data monitored from each bed is stored in a circular memory buffer to allow recording of pre-trigger waveform data. On a typical modern PC, system resources will allow for a fairly substantial buffer (approximately 30-60 minutes depending on system specifications). A detailed discussion of programming the SDN card may be found in [5].

The third task requires relatively swift computation of some index relating to the degree of irregularity in the ECG waveform. Motivated by [3] and [4] we chose to implement a spectral power computation and a nonlinear complexity measure. These are discussed in Section 2.1 and Section 2.2.

Finally, the fourth task is also a trivial programming exercise. As currently implemented our algorithm writes the pre-trigger data to disk before the (still incoming) post-trigger data. If the amount of pre-trigger data is substantial this may be problematic, in which case it is preferable to do the reverse (see [2]).

2.1. Spectral power estimation

The fast Fourier transform (FFT) [6] allows for extremely rapid computation of a time series spectral power content. Following the advice of [2] we found that computing the proportion of power between 3 and 6 Hz gave a good indication of a signal’s frequency content. When the root-mean-square power content between 3 and 6 Hz exceeded 0.75 we triggered data recording. Note that in [2] recording was triggered if the proportion of signal power in the 3-6 Hz range exceeded 0.75 for more than 2 seconds. We chose to trigger recording if any sample had more than 75% power in the 3-6 Hz range.

We found that this method was fast and could identify potential arrhythmia episodes reliably without excessive false positives (for the purposes of data collection a large number of false positive is only an inconvenience, and is to be preferred to misidentified arrhythmia).

2.2. Nonlinear complexity

Recently it has been noted that nonlinear complexity provides a good specificity and significance for separating sinus rhythm from VF and ventricular tachycardia (VT) [4]. Furthermore, we have found some evidence (for example [7]) to support the hypothesis that VF may best be described as a nonlinear dynamical system. Because of this we chose to implement nonlinear complexity as an alternative index to trigger recording.

Nonlinear complexity is a measure of the structural complexity of a time series. It is an information theoretic measure popular in nonlinear dynamical systems theory. The complexity of a time series is (approximately) how
much compression may be achieved when applying some computational data compression algorithm. Regular rhythms are predictable and therefore may be substantially compressed (and therefore have a low complexity), irregular rhythms are less predictable and may be compressed less (a high complexity).

For example, sinus rhythm is regular and predictable — one would therefore expect a sinus rhythm time series to have a low complexity measure. VF and VT however, are irregular and unpredictable — time series recordings ofVF and VT would be expected to have a higher complexity. This has been shown experimentally [4]. Details of algorithms to calculate complexity may be found in [4] and the references therein.

2.3. Comments

Although non-linear complexity has been shown to offer good significance and specificity for identification of VF and VT, we found that the algorithm (as we implemented it) to be substantially slower than a FFT technique. For this reason we prefer the FFT power spectral estimation method for automatic recording of potential arrhythmia. Although the specificity of this algorithm is possibly lower, we found this to be only a minor inconvenience.

3. Typical results

Our data collection protocol has only recently been finalized and data collection has been underway for a comparatively short time. In the near future we hope to perform substantial analysis (both linear and nonlinear) on time series of spontaneous VF and pre-VF recordings.

In this paper we present representative recordings of arrhythmia produced by our data collection facility. Figure 2 shows segments of spontaneous VT, and restoration of sinus rhythm. Figure 3 shows initiation of spontaneous VF following VT, for which the patient was successfully defibrillated after two shocks.

4. Conclusions

The method we have described here may be used to automatically record data during spontaneous cardiac arrhythmia and the data leading up to these episodes. We intend to use this facility to build up a library of VF and VT episodes. We will then be able to examine ECG before the onset of VF for potential signatures using traditional linear as well as non-linear analysis techniques [7]. Such data will be invaluable for future research into the spontaneous evolution of cardiac arrhythmia.

Acknowledgements

We wish to thank R. Clayton for many helpful discussions and P. Kranich of Agilent Technology (formerly Hewlett-Packard, GmbH) for help with the HP hardware. We are grateful for the help and co-operation of the staff of the CCU of the Royal Infirmary of Edinburgh. The Scottish Higher Education Funding Council (SHEFC) currently funds this research through a Research Development Grant, No. RDG/078.
Figure 3. An example of a recording of spontaneous VF using the methods described in this paper. The horizontal axes are time (in seconds) and the vertical axes are surface ECG voltage (in mV). This trace shows the spontaneous initiation of VT, transition to VF and a subsequent (unsuccessful) defibrillation shock. A second defibrillation shock (not shown) was successful. Data has been recorded at 500 Hz and 10 bits. Recording was triggered (using the FFT algorithm) at the start of VT (approximately 28-29 seconds on the time axes marked).

References


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